Distributed Information Management

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PARIS LODRON UNIVERSITY SALZBURG

Part I

Data Management

Literature, Sources, and Credits

Literature:

- Silberschatz et al. *Database System Concepts*. McGraw Hill, Sixth Edition, 2010.
- Wiese. *Advanced Data Management*. De Gruyter Oldenbourg, 2015.

Credits: These slides are partially based on slides of other lectures.

- Nikolaus Augsten, University of Salzburg, Austria (Credits also for valuable discussions and guidance).
- Andrew Pavlo, Carnegie Mellon University (CMU), USA.

Introduction

Motivation

The amount of data is growing rapidly in many different domains.

We do not collect data to simply store it, but we want to

- access it fast at any time and from any place,
- search it (for exact and similar patterns),
- aggregate it (partially),
- join it with other data,
- have multiple users working on the data concurrently,
- make sense out of it.

Motivation

“But I can organize my data without the overhead of a dedicated system!”

Theoretically yes, but this implies:

- Organizing your data in multiple independent (plain) files.
- Other users may have trouble to understand your organization.
- Taking care of all the requirements yourself.
- You drop flexibility and scalability.

What can possibly go wrong?

Example Application

Managing the DAS faculty members using CSV files and Python3.

Members: (name;employment;department;)

```
Daniel Kocher;Postdoc. Researcher;CS;
Thomas Hütter;Postdoc. Researcher;CS;
Tijn De Vos;PhD Student;CS;
Christoph Kirsch;Full Professor;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Professor;AIHI;
Bernd Resch;Assoc. Professor;GI;
Simon Blatt;Assoc. Professor;Mathematics;
```

Departments: (name;location;)

```
CS;Science City Salzburg;
AIHI;Science City Salzburg;
GI;Science City Salzburg;
Mathematics;Faculty of Nat. Sciences (NAWI);
```

Example Application

Query: Find the names of all members that belong to the “CS” department.

```
if __name__ == "__main__":
  with open("members.csv", "r") as fin:
    for line in fin.readlines():
      parts = line.split(";")

      name = parts[0]
      employment = parts[1]
      department = parts[2]

      if department == "CS":
        print(name)
```

Problems in Data Management

Redundancy and Inconsistency:

- Several copies of a datum may exist (possibly stored differently).
- **Redundancy:** Higher storage requirements. How about accessing the data?
  $\Rightarrow$ Multiple file accesses (which is slow).
- **Inconsistency:** What happens if you have to update the data?
  $\Rightarrow$ We must not forget a single copy.
- **Goal:** Minimize redundancy and prevent inconsistency.

Example: Update “CS” to “Computer Science”.

Example Application

Query: Update “CS” to “Computer Science”.

Members: (name;employment;department;)

```
Daniel Kocher;Postdoc. Researcher;CS;
Thomas Hütter;Postdoc. Researcher;CS;
Tijn De Vos;PhD Student;CS;
Christoph Kirsch;Full Professor;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Professor;AIHI;
Bernd Resch;Associate Professor;GI;
Simon Blatt;Assoc. Professor;Mathematics;
```

Departments: (name;location;)

```
Computer Science;Science City Salzburg;
AIHI;Science City Salzburg;
GI;Science City Salzburg;
Mathematics;Faculty of Nat. Sciences (NAWI);
```

Problems in Data Management

Data Access and Analysis:

- We want to analyze our data. How to link related data?
  $\Rightarrow$ Each analysis requires a tailored program.
- **Goal:** Generic analysis and linkage of related data.

Example: List all members that belong to the “AIHI” department with their location.

Example Application

Query: List all members that belong to the “AIHI” department with their location.

Members: (name;employment;department;)

```
Daniel Kocher;Postdoc. Researcher;CS;
Thomas Hütter;Postdoc. Researcher;CS;
Tijn De Vos;PhD Student;CS;
Christoph Kirsch;Full Professor;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Professor;AIHI;
Bernd Resch;Associate Professor;GI;
Simon Blatt;Assoc. Professor;Mathematics;
```

Departments: (name;location;)

```
Computer Science;Science City Salzburg;
AIHI;Science City Salzburg;
GI;Science City Salzburg;
Mathematics;Faculty of Nat. Sciences (NAWI);
```

Problems in Data Management

Data Integrity Issues:

- Updates may violate the integrity of your data.
- How do you ensure data integrity?
  $\Rightarrow$ Each single application must respect all consistency constraints.
- **Goal:** Global definition and monitoring of consistency constraints.

Example: Insert “Nikolaus Augsten” as member of the “AIHI” department.

Problems in Data Management

Concurrency Issues:

- Multiple users should be able to access and update the data simultaneously. How do you ensure consistency over all applications that access the data?
- **Anomalies:** Inconsistencies, e.g., lost updates.
- **Efficiency:** If one user locks a file, then the other user must wait.
- **Goal:** Out-of-the-box multi-user operation without anomalies.

Example: User A inserts “Nikolaus Augsten” as member while user B inserts “Ana Sokolova” as member of the “CS” department simultaneously.

Example Application

Scenario: User A inserts “Nikolaus Augsten” as member while user B inserts “Ana Sokolova” as member of the “CS” department simultaneously.

Members: (name;employment;department;)

```
Daniel Kocher;Postdoc. Researcher;CS;
Thomas Hütter;Postdoc. Researcher;CS;
Tijn De Vos;PhD Student;CS;
Christoph Kirsch;Full Professor;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Professor;AIHI;
Bernd Resch;Associate Professor;GI;
Simon Blatt;Assoc. Professor;Mathematics;
Ana Sokolova;Associate Professor;CS;
```

Problems in Data Management

Atomicity and Recovery:

- Data must neither be lost nor inconsistent when the system crashes.
- **Atomicity:** Data may be inconsistent if an operation is only applied partially
  $\Rightarrow$ Execute an operation in an all-or-nothing manner.
- **Recovery:** Backup of data may not reflect the latest state.
- **Goal:** Prevent data loss and inconsistencies by design.

Example: Update all "CS" members to belong to the "Computer Science" department. Your system crashes in between "Tijn De Vos" and "Christoph Kirsch".

Example Application

Scenario: Update all “CS” members to belong to the “Computer Science” department. Your system crashes in between “Tijn De Vos” and “Christoph Kirsch”.

Members: (name;employment;department;)

```
Daniel Kocher;Postdoc. Researcher;Computer Science;
Thomas Hütter;Postdoc. Researcher;Computer Science;
Tijn De Vos;PhD Student;Computer Science;
Christoph Kirsch;Full Professor;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Professor;AIHI;
Bernd Resch;Associate Professor;GI;
Simon Blatt;Assoc. Professor;Mathematics;
Ana Sokolova;Associate Professor;CS;
```

Problems in Data Management

Other Issues:

- **Efficiency:** Efficient algorithms are required to analyze large amounts of data.
- **General-purpose:** The problems of application developers will partially overlap.
- **Security issues:** Flexible and fine-grained access rights for multiple users.

Database Management Systems

A **database management system** (DBMS) is

(i) a collection of interrelated data, the **database**, and

(ii) a set of programs to access the data.

In other words, you do not have to care about how to store the data (physically), how to analyze it (efficiently), how to (partially) update data, or how to deal with multiple users. A DBMS organizes all this for you.

DBMSs are at the core of many applications.

When Not to Use a DBMS

- The data are too complex to model it.
- Specific requirements like real-time queries or special operations.
- The overhead of a DBMS is too high or unnecessary.
- No or low return on investment (ROI).

One Size Fits All?

General-Purpose DBMS

A DBMS that tries to fit as many application scenarios as possbile with a single system. This implies higher complexity but also a large user base.

Examples:

- PostgreSQL (open source)
- MySQL (open source)
- MonetDB (open source)
- SQLite (open source)
- IBM DB2 (closed source)
- Oracle Database (closed source)
- Microsoft SQL Server (closed source)
- …

General-Purpose DBMS

“But this sounds good, no?”

Problems:

- Unnecessary overhead (e.g., recovery or strong consistency)
- Limited performance
- Application-specific operations are not supported natively
- Limited flexibility

One Size Fits All (OSFA)

"One Size Fits All": An Idea Whose Time Has Come and Gone

Michael Stonebraker[1] and Ugur Cetintemel (2005)

A one size fits all database doesn't fit anyone

Werner Vogels[2] (2018)

[1] Database Systems Researcher at the MIT. Won the Turing Award in 2014.
[2] Computer Scientist and CTO at Amazon.

Special-Purpose DBMS

A DBMS that is tailored to fit a specific purpose best, i.e., provide all the functionality that is required while also providing the best performance and flexilibity (with respect to the specific application domain).

Synonyms: Specialized DBMS, purpose-built DBMS.

Special-Purpose DBMS

Temporal Data: A temporal DBMS is optimized to manage and analyze data that references time (i.e., they are timestamped). For example, a time series $x = \langle x_{t_1}, x_{t_2}, \ldots, x_{t_n} \rangle$ is often a sequence of n data points that are spaced at strictly increasing times ($t_i < t_{i+1}$ with $i = 1, \ldots, n-1$).

Requirements:

- Exact/Approximate matching of (parts of) time series.
- Efficient compression mechanisms.
- Serve specific aspects like valid time or transaction time.
- ...

Special-Purpose DBMS

Real-Time Data: A real-time DBMS manages data that is changed continuously. A DBMS that operates in real time answers the queries within a guaranteed time frame (the response time, i.e., it has a deadline).

Requirements:

- Answer every query in a given time frame.
- Query scheduling (or queuing).
- Consistency may not be that important.
- …

Special-Purpose DBMS

Process Mining Data: Process mining engines manage business event logs. An example event log is the sequence of activities if you place an order in some online shop. These systems are required to analyze large amounts of data in real time.

Requirements:

- Optimized, domain-specific language.
- Real-time performance for best user experience.
- …

Special-Purpose DBMS

Multiple specific aspects may need to be combined to serve a novel application scenario. This may also result in a new special-purpose DBMS.

A modern application is not monolithic, i.e., different DBMSs may be used to implement different parts of an application.

One Size Fits All

Towards a One Size Fits All Database Architecture

Jens Dittrich[3] and Alekh Jindal. 2011.

One Size Fits all, Again! The Architecture of the Hybrid OLTP&OLAP Database Management System HyPer

Alfons Kemper[4] and Thomas Neumann[5]. 2011.

[3] Database Systems Researcher at Saarland University.
[4] Database Systems Researcher at the TU Munich co-author of the book *Datenbanksysteme*.
[5] Database Systems Researcher at the TU Munich.

Database Fundamentals

Basic Terminology

Data are facts that are to be stored.

Information is data combined with semantics (meaning).

Knowledge is information combined with an application.

Example Application

What are data, information, and knowledge in our example?

Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS
Simon Kirchgasser	PhD Student	AIHI
Roland Kwitt	Full Prof.	AIHI
Bernd Resch	Assoc. Prof.	GI
Simon Blatt	Assoc. Prof.	Math.

Departments:

name	location
CS	Science City Salzburg
AIHI	Science City Salzburg
GI	Science City Salzburg
Math.	Faculty of Nat. Sciences (NAWI)

Basic Terminology

A **database** (DB) is a collection of interrelated data.

Metadata provides us with information about the structure of a database. All the metadata are stored in a **catalog**.

A **database system** (DBS) is also referred to as the combination of a database, the corresponding metadata, and a DBMS (which in this case only provides the set of programs). The terms DBS and DBMS are often used interchangeably.

Example Application

Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Catalog:

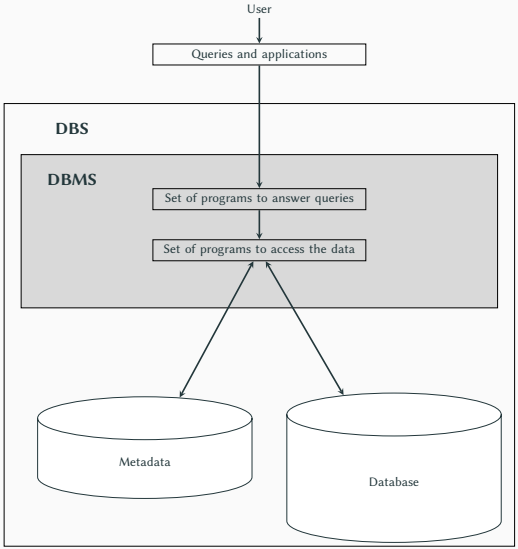
Tables Metadata:

relation	rowCount
Members	8
Departments	4

Columns Metadata:

columnName	dataType	relation
name	TEXT	Departments
year	INTEGER	Departments
name	TEXT	Members
…	…	…

Database System



More Terminology

A **table** consists of multiple **tuples**, each of which is a sequence of **attributes**. Informally, a tuple can be imagined as a row of a table, whereas an attribute can be imagined as a column.

A **key** is subset of attributes. A **primary key** is a key of minimum length that uniquely identifies a tuple. A **foreign key** is a reference to a primary key.

More Terminology

A **schema** describes the overall structure of the data (often using tables) and is typically stable (i.e., rarely modified).

An **instance** is the information that is stored at a particular point in time (e.g., of a single tuple, a table, or an entire database). The instance may be frequently subject to changes.

Each level has its own schema with the logical schema being the most important one.

A **valid instance** satisfies all structural requirements and consistency constraints.

Data Modeling

Data-Definition Language (DDL): Specify the structure of your data and the consistency constraints that are enforced.

- **Schema:** Describes the structure of your data and how the data are interrelated, e.g., a department has 3 columns: name, location, and year.
- **Consistency Constraints:** Describe integrity constraints that must be satisfied at any given point in time, e.g., the year of establishment is an integer ≥ 1622.

Example Application

Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Pseudo-DDL (simplified):

```
CREATE TABLE Members (
  name TEXT KEY,
  employment TEXT,
  department TEXT REFERENCES(Departments.name)
)
```

```
CREATE TABLE Departments (
  name TEXT KEY,
  location TEXT,
  year INTEGER (>= 1622)
)
```

Data-Manipulation Language (DML): Query and manipulate your data.

- **Query Language:** Allows you to query your data without modifying it, e.g., get all members of the "CS" department or get all departments located in the "Science City Salzburg".
- **Manipulation Language:** Allows you to modify your data, e.g., insert a new professor, delete an existing person, update the name of a particular department.

A **query** is a statement that requests some information. Informally, your query "asks" and the database system answers by returning the corresponding information.

Caveat: The term query language often refers to both DML parts.

Example Application

Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Pseudo-DML (simplified):

```
SELECT department FROM Members
WHERE name = 'Daniel Kocher'

SELECT name FROM Members
WHERE employment = 'Postdoc.'
```

```
INSERT INTO Members
VALUES ('Nikolaus Augsten', 'Full Prof.', 'CS')

UPDATE Departments
SET name = 'Computer Science'
WHERE name = 'CS'
```

Query Languages

Imperative Languages[6]**:** Describe a sequence of operations to retrieve the desired data.

Declarative Languages: Describe what data you are interested in (no specific steps).

Pure Languages: Form the (theoretical) foundation underneath the languages that are used in practice. Examples include relational algebra (imperative) or tuple calculus (declarative).

Our Focus: Declarative languages (and a bit of imperative languages).

[6] Imperative and procedural are often used synonymously.

Real-World Analogy

Send someone to the supermarket to get milk.

The SQL Query Language

The **Structured Query Language (SQL)** was developed by IBM and is the de-facto standard language in database systems.

SQL is a declarative query language and includes DDL and DML elements.

The SQL standard (last revision: 2016) comprehensively summarizes all elements.

Inventing new approaches is like *"trying to swim up the Niagara Falls".*

Michael Stonebraker in Information Age. 2010.

Example Queries in SQL

Data Definition:

```
CREATE TABLE Members (
  name VARCHAR(50) PRIMARY KEY,
  employment VARCHAR(50),
  department VARCHAR(100) REFERENCES Departments(name)
);
```

```
CREATE TABLE Departments (
  name VARCHAR(100) PRIMARY KEY,
  location VARCHAR(75),
  year INTEGER NOT NULL CHECK(year >= 1622)
);
```

- **`VARCHAR(n)`**, **`INTEGER`:** Domain of a single column (data types).
- **`NOT NULL`**, **`CHECK`:** Constraints on a single column.
- **`PRIMARY KEY`**, **`REFERENCES`:** Constraints on an entire table.

Example Queries in SQL

Queries:

```
SELECT department FROM Members
WHERE name = 'Daniel Kocher';

SELECT name FROM Members
WHERE employment = 'Postdoc.';
```

- **SELECT:** Specifies the column to retrieve.
- **FROM:** Specifies the tables to consider.
- **WHERE:** Specifies the condition(s) the result must satisfy.

Example Queries in SQL

Queries:

```
INSERT INTO Members(name, employment, department)
VALUES ('Nikolaus Augsten', 'Full Prof.', 'CS');

UPDATE Departments SET name = 'Computer Science'
WHERE year = 2022;
```

- **INSERT INTO** ... **VALUES:** Adds new tuple to a table based on the given values.
- **UPDATE** ... **SET:** (Partially) changes the values of a tuple.

Data Abstraction

Abstraction: Hide the complexity of the system (from people without deep computer science background) while providing all the functionality. Everyone should be able to use a database system.

Three Levels of Data Abstraction (bottom-up):[7]

1. **Physical: How** the data is stored (e.g., as sequence of bytes on hard disk, SSD, …).
2. **Logical: What** data are stored and what relationships exist.
3. **View: Specific views** on the data (e.g., on a specific part of the entire database).

[7] Cf. also ANSI/SPARC architecture.

Three Levels of Data Abstraction

The **physical level** defines the **physical** data structures that are used to **store**, **organize**, and **access** the data **efficiently**. Examples include tables or access paths (e.g., using so-called indexes as shortcuts).

The **logical level** defines the **schemata** and **constraints** of the entire database. Physical data structures may be used underneath, but the user does not have to know them. $\Rightarrow$ **physical data independence**.

The **view level** reduces the complexity by providing only **information that is necessary for the respective user**. Irrelevant data are not shown and the focus is to simplify the interaction with the database system.

The Physical Level – Example

What is a **physical representation**[8] of our **Members table?**

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS
Simon Kirchgasser	PhD Student	AIHI
Roland Kwitt	Full Prof.	AIHI
Bernd Resch	Assoc. Prof.	GI
Simon Blatt	Assoc. Prof.	Math.

```
Daniel Kocher;Postdoc.;CS;
Thomas Hütter;Postdoc.;CS;
Tijn De Vos;PhD Student;CS;
Christoph Kirsch;Full Prof.;CS;
Simon Kirchgasser;PhD Student;AIHI;
Roland Kwitt;Full Prof.;AIHI;
Bernd Resch;Assoc. Prof.;GI;
Simon Blatt;Assoc. Prof.;Mathematics;
```

A sequence of tuples with special characters as delimiters for attributes (;) and tuples (newline), respectively.

[8] This is an example – there are many possible physical representations.

The Logical Level – Example

What is a **logical representation**[9] of our **Members table?**

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS
Simon Kirchgasser	PhD Student	AIHI
Roland Kwitt	Full Prof.	AIHI
Bernd Resch	Assoc. Prof.	GI
Simon Blatt	Assoc. Prof.	Math.

```
CREATE TABLE Members (
  name VARCHAR(50) PRIMARY KEY,
  employment VARCHAR(50),
  department VARCHAR(100) REFERENCES Departments(name)
);
```

Our table consists of three attributes with type definitions (**`VARCHAR(n)`**), constraints (**`PRIMARY KEY`**), and interrelationships (**`REFERENCES`** `Departments(name)`).

[9] Again, this is an example – there exist multiple different logical representations.

The View Level – Example

What is a **view** of our **Members table?**

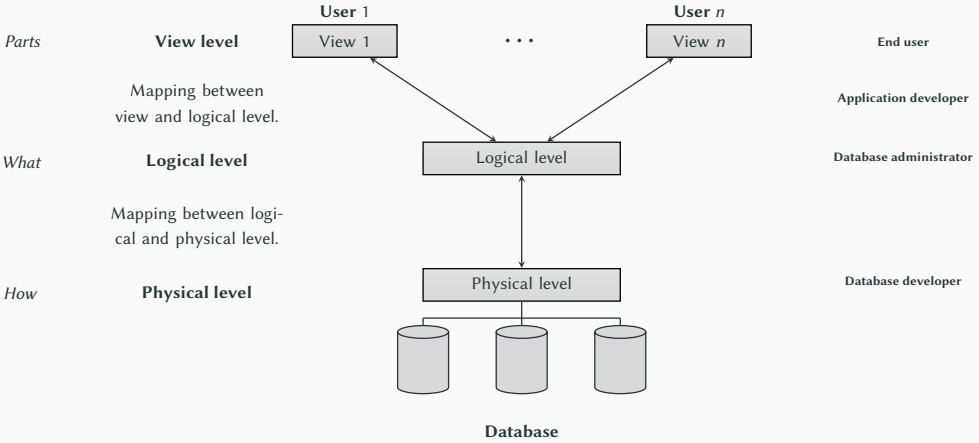
name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS
Simon Kirchgasser	PhD Student	AIHI
Roland Kwitt	Full Prof.	AIHI
Bernd Resch	Assoc. Prof.	GI
Simon Blatt	Assoc. Prof.	Math.

name	employment	department
Tijn De Vos	PhD Student	CS
Simon Kirchgasser	PhD Student	AIHI

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS

Secretaries at the university may only have access to specific members depending on their area of responsibility (PhD students) or affiliation (CS department).

Three Levels of Data Abstraction



Mappings are used to link the abstraction levels.

Instance vs. Schema Revisited

A **schema** describes the overall structure of the data (often using tables) and is typically stable (i.e., rarely modified).

An **instance** is the information that is stored at a particular point in time (e.g., of a single tuple, a table, or an entire database). The instance may be frequently subject to changes.

Each level has its own schema with the logical schema being the most important one.

A **valid instance** satisfies all structural requirements and consistency constraints.

Instance vs. Schema Revisited

Schemata:

Members:

name	employment	department

Departments:

name	location	year

Instances:

Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Data Independence

Logical Data Independence: The ability to **update the logical schema transparently**, i.e., no change on the view level is required.

Physical Data Independence: The ability to **update the physical schema transparently**, i.e., no change on the logical level is required.

Benefits:

- Only the mapping between the levels need to be adapted.
- No change in the application required (it operates on the views).

(Declarative) Query Processing

Example SQL Query (+ Result):

```
SELECT name FROM Members
WHERE employment = 'Postdoc.';
```

name
Daniel Kocher
Thomas Hütter

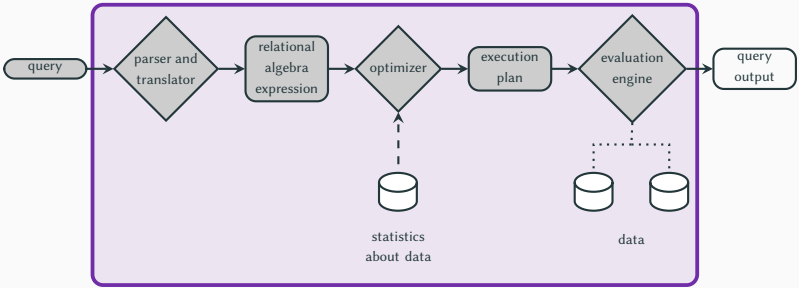
Query processing describes the process of extracting data from a database. In other words: What happens in a database when we issue a (declarative) query?

(Declarative) Query Processing

```
SELECT name FROM Members
WHERE employment = 'Postdoc.';
```

⇒ ? ⇒

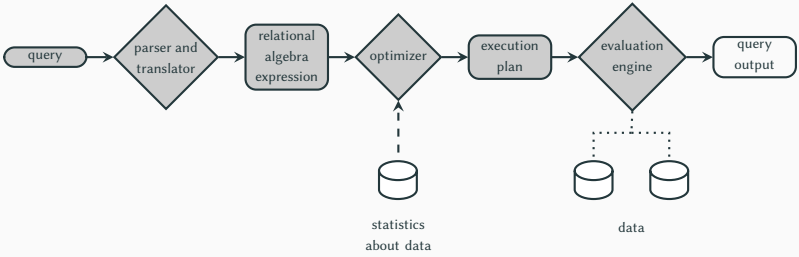
name
Daniel Kocher
Thomas Hütter



(Declarative) Query Processing

On a high level, **three major components** are used to process a query:

1. **Parser:** Translates the query into an internal representation.
2. **Optimizer:** Chooses the most efficient way to evaluate the query.
3. **Evaluation Engine:** Executes the evaluation plan and returns the result.



(Declarative) Query Processing

An evaluation plan typically consists of multiple operation. Optimization is done based on the **estimated costs** of all involved operations.

For a given query, multiple valid **evaluation plans** may exist and must be **compared efficiently** (with respect to their estimated costs).

The estimated costs consider **many different factors** including access to hard disk, time to execute the query on the CPU, or network communication costs.

Data Models

Types of Data Models

3 types of data models that are somewhat related to the 3 levels of data abstraction.

Conceptual data models: High level, i.e., only the schema is reflected but no instances. Related to the view level. Examples include Entity-Relationship (ER) and Unified Modeling Language (UML) models.

Logical data models: Depicts the instances and can be used to implement a database. Related to the logical level. Examples include the relational and the object-based models.

Physical data models: Low level, i.e., as close to the physical storage as possible. Related to the physical level and is typically system-specific.

Types of Data Models – Examples

Logical Model (Relational):

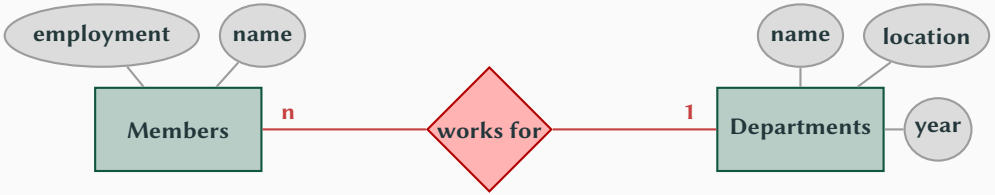
Members:

name	employment	department
Daniel Kocher	Postdoc.	CS
Thomas Hütter	Postdoc.	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Conceptual Model (ER):



Relational Data Model

Intuitive and **widely used** model. An example of a **record-based** model.

A **collection of relations (tables) stores records of data as rows.** A **tuple (row)** is an **entity** of the real world, an **attribute (column)** is a **property** of an entity. The **structure** of a record is **fixed.**

A **relation** has a **name** and a **set of (unique) attributes**. An **attribute** has a **name** and a **predefined domain**, i.e., values originate from a specific domain.

Tables are **filled row-wise** and a **row** represents the **state of an entity.**

The set of columns is called **relation schema**, and the set of relation schemata over all tables is called the **database schema**.

Intrarelational constraints: Dependencies inside a single table, Σ_i

Interrelational constraints: Dependencies between different tables, Σ

Relation schema: $R_i = (\{A_{i1}, A_{i2}, \ldots, A_{im}\}, \Sigma_i)$[10].

Database schema: $D = (\{R_1, R_2, \ldots, R_n\}, \Sigma)$.

[10] A_{ij} ... Name of the j-th attribute (column) of the i-th relation (table).

Relational Data Model – Example

Members:

name	employment	year of empl.	department
Daniel Kocher	Postdoc.	2021	CS
Thomas Hütter	Postdoc.	2022	CS
…	…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

Relation schemata:

$$\text{Members} = (\{\text{name}, \text{employment}, \text{year of empl.}, \text{department}\}, \{\text{name}, \text{year of empl.} \rightarrow \text{employment}\})$$

$$\text{Departments} = (\{\text{name}, \text{location}, \text{year}\}, \{\text{name}, \text{year} \rightarrow \text{location}\})$$

Database schema:

$$\text{DASFaculty} = (\{\text{Members}, \text{Departments}\}, \{\text{Members.department} \subseteq \text{Departments.name}\})$$

Relational Data Model

Normalization: Reduce anomalies (which lead to inconsistencies) by distributing attributes among tables and linking them using **foreign key constraints**.

Referential Integrity: Values of foreign keys exist as values in the referenced table, i.e., the referenced table contains at least one tuple that holds the value of the foreign key.

Relational Data Model – Example[11]

Members:

id	name	employment	year of empl.	department
1	Daniel Kocher	Postdoc.	2021	CS
2	Thomas Hütter	Postdoc.	2022	CS
3	Tijn De Vos	PhD Student	2020	CS
4	Christoph Kirsch	Full Prof.	1995	CS
5	Simon Kirchgasser	PhD Student	2016	AIHI
6	Roland Kwitt	Full Prof.	2019	AIHI
7	Bernd Resch	Assoc. Prof.	2018	GI
8	Simon Blatt	Assoc. Prof.	2017	Math.

Departments:

id	name	location	year
201	CS	Science City Salzburg	2022
202	AIHI	Science City Salzburg	2022
203	GI	Science City Salzburg	2010
204	Math.	NAWI	1967

[11] This is an example with synthetic data

Relational Data Model – Example

Members:

id	name	employment	year of empl.	department
1	Daniel Kocher	Postdoc.	2021	CS
2	Thomas Hütter	Postdoc.	2022	CS
3	Tijn De Vos	PhD Student	2020	CS
4	Christoph Kirsch	Full Prof.	1995	CS
5	Simon Kirchgasser	PhD Student	2016	AIHI
6	Roland Kwitt	Full Prof.	2019	AIHI
7	Bernd Resch	Assoc. Prof.	2018	GI
8	Simon Blatt	Assoc. Prof.	2017	Math.

Departments:

id	name	location-id	year
201	CS	**402**	2022
202	AIHI	**402**	2022
203	GI	**402**	2010
204	Math.	**403**	1967

Locations:

id	name
402	Science City Salzburg
403	NAWI

Relational Data Model

Drawbacks:

- Relations may not be optimal to represent the data.
- Everything is a relation (semantic overloading).
- Homogeneous structure of data.
- Limited flexibility and data types.

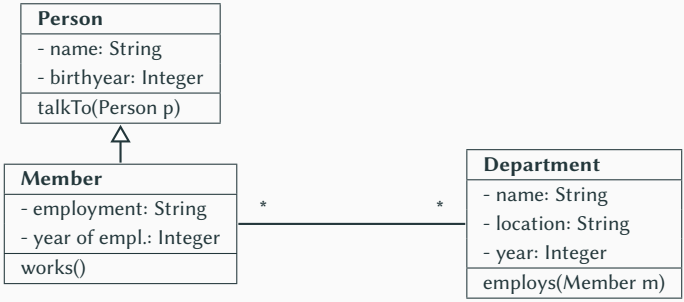
Drawbacks and new challenges gave rise to **non-relational data models**.

Object-Based Data Model

Many programming languages are object-oriented, i.e., based on the concept of objects.

Objects contain data and provide functionality, and interact with each other (e.g., like human beings in the real world).

Example Objects:



Object-Based Data Model

Three Options:

1. **Object-relational data model:** Extends relational data model with object-oriented features.
2. **Object-relational mapping (ORM):** Maps objects to tuples in the relational model and handles the translation.
3. **Object-oriented data model:** Implements an object-based data model natively.

Key-Value Data Model

Prototype of a **schemaless** model where each tuple is a pair of two strings (k, v). k is a **unique key** that is associated with an arbitrary **value** v.

Data are accessed using the key and values are not interpreted by any means.
Example operations:

- `put(k, v)`: Inserts a new pair key-value pairs (k, v)
- `get(k)`: Retrieves the value associated with k.
- `delete(k)`: Deletes the tuple(s) associated with k.

Caveat: In programming often referred to as hash table or dictionary (Python).

Key-Value Data Model

Only keys can be searched, **values cannot be searched.** Combinations of values must be done by the application that accesses the data.

Easy to distribute ⇒ Good for **data-intensive applications.**

Example Key-Value Store:

UserID		Shopping Cart
1002	→	Shoe, Jordans, red, 37 # Computer game “Diablo”, Blizzard # Headset, Razer, Kraken Kitty
1003	→	Wilson American Football, NFL, Replica # Hail Mary, Gloves Receiver, 2.0, Black & White
1004	→	Book “Database System Concepts”, 7th Edition, Silberschatz
…		…

Document-Based Data Model

A document stores data in a semi-structured and nested text format (e.g., XML or JSON).

Each document has a unique identifier, but the value is a document structured in a specific format that is interpretable (as opposed to a key-value store).

JavaScript Object Notation (JSON): Human-readable text format for data structures. A JSON document consists of possibly nested key-value pairs.

Document-Based Data Model

A JSON document consists of a JSON object, which is enclosed by curly braces, { . . . }. Inside, keys and the corresponding values are separated by a colon, and a value can be a JSON object itself.

Example Document Store:

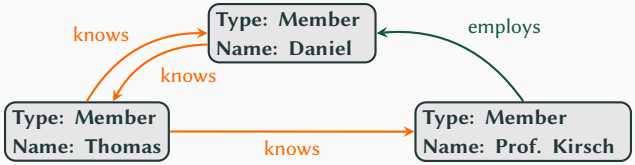
UserID	→	Shopping Cart
1002	→	{ “1”: { “type”: “Shoe”, “name”: “Jordans”, “color”: “red”, “size”: 37 }, “2”: { “type”: “Computer game”, “name”: “Diablo”, “publisher”: “Blizzard” }, “3”: { “gear”: “Headset”, “producer”: “Razer”, “model”: “Kraken Kitty” } }
…		…

Graph-Based Data Model

Graphs: Informally, graphs are structures that represent data (as nodes) and their interrelation (as edges in between) by design. Both nodes and edges may carry information. Efficient graph operations are supported natively.

Data and their relationship are distinct naturally (cf. semantic overloading of the relational data model).

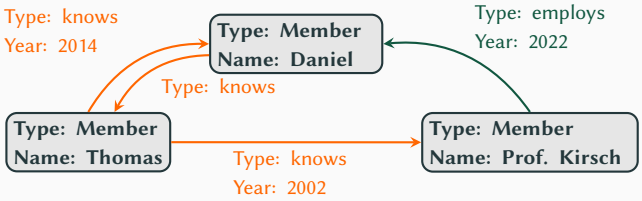
Example Graph:



Graph-Based Data Model

Property Graph Model: Multiple types for nodes/edges (multi-relational), each of which may contain multiple properties (attributes) as name-value pairs (similar to key-value pairs).

Example Property Graph:



Extensible Record Data Model

Also referred to as **wide column data model** and a generalization of Google's BigTable[12] system.

Table cells are represented as (2-dimensional) key-value pairs, with row (unique) and column (repeatedly) being the keys.

Example: Access table cell `(4:employment)`.

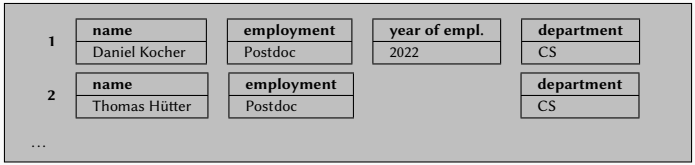
id	name	employment	year of empl.	department
1	Daniel Kocher	Postdoc	2022	CS
2	Thomas Hütter	Postdoc	NULL	CS
3	Tijn De Vos	PhD Student	2020	CS
4	Christoph Kirsch	Full Prof.	1995	CS
5	Simon Kirchgasser	PhD Student	2016	AIHI
…	…	…	…	…

[12] Chang et al. *Bigtable: A Distributed Storage System for Structured Data.* OSDI, 2006.

Extensible Record Data Model

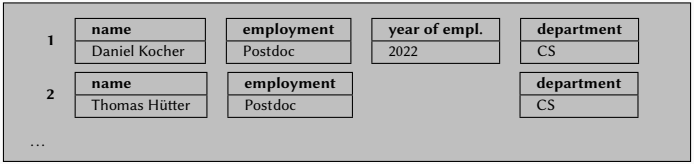
id	name	employment	year of empl.	department
1	Daniel Kocher	Postdoc	2022	CS
2	Thomas Hütter	Postdoc	NULL	CS
3	Tijn De Vos	PhD Student	2020	CS
4	Christoph Kirsch	Full Prof.	1995	CS
5	Simon Kirchgasser	PhD Student	2016	AIHI
…	…	…	…	…

considered as

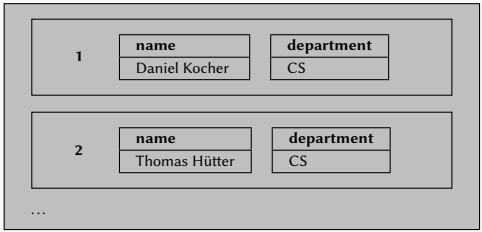


Extensible Record Data Model

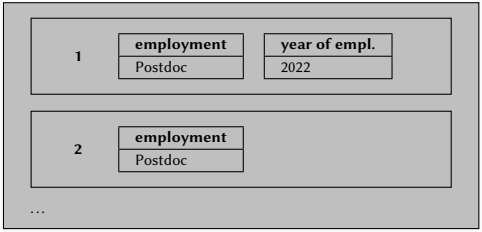
Column Families: Group columns that are accessed simultaneously (at the same time).



PersonInfo:



EmploymentInfo:



Extensible Record Data Model

Encourages de-normalization (redundancy) for higher performance and provides **more flexibility**, i.e., every row may be composed of different columns.

The query workload defines how the data is modeled ⇒ Know your workload.

Full key access to a value: `(<rowid>:<columnfamily>:<columnname>)`.
For example: `(2:EmploymentInfo:employment)` returns `Postdoc`.

Array-Based Data Model

Complex structures (like 2-dimensional satellite or *n*-dimensional sensor data) are organized along multiple dimensions.

An array cell contains a tuple of a specific length and a tuple element may contain a value or another array (allowing arbitrary nestings).

Specialized array functionality is natively supported (e.g., joins and aggregations).

Workloads & Challenges

Outline

- New data management **challenges**.
- Basics of **distributed** database systems (also compared to parallel DBS).
- **Consistency guarantees:** ACID vs. BASE.
- The **CAP** Theorem.
- **Workloads:** OLTP vs. OLAP, batch vs. stream processing.

New Data Management Challenges

- Data may be organized in **complex structures** (e.g., graphs).
- Data may be **schemaless** (e.g., not comply to a fixed schema).
- Data may be **sparse** (e.g., values may be non-existent).
- Data or schema may be **constantly changing** (e.g., schema evolution).
- Data may be **distributed over multiple machines.**
  - Access must be **transparent** (i.e., user need not know where data resides).
  - Systems must **scale horizontally** (i.e., new machines come and go).
  - Systems must cope with **large data volumes**.

New Data Management Challenges

NoSQL (Not Only SQL):

- Class of non-relational DBSs.
- Weaker consistency guarantees (e.g., BASE[13])
- Support for schema independence.
- Highly scalable.

NewSQL:

- Class of relational DBSs.
- Aim to
  - Provide NoSQL-like scalability (for OLTP[9] workloads).
  - Retain strong consistency guarantees like RDBMS (e.g., ACID[9]).

[13] We will cover this term subsequently.

Parallel Database Systems

Parallel database management systems (PDBMSs) have multiple processors and hard disks that are connected via a fast interconnection.

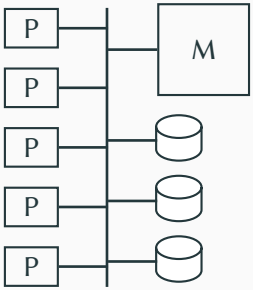
Performance characteristics:

- **Throughput:** Number of tasks (e.g., queries) that can be completed in a given time frame. Example: Queries per seconds.
- **Response time:** Time it takes to complete a single task (e.g., query).

Parallel Database System Architectures

Shared memory DBMSs have many processors and disks that share a common memory (typically via a bus).

- \+ Efficient communication between processors ($< 1\mu s$).
- \- Limited scalability (≤ 64 processors; interconnection to memory becomes the bottleneck).

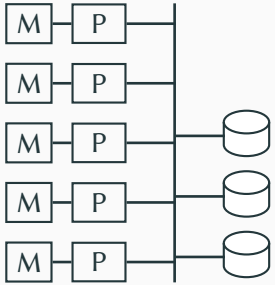


P . . . processor, M . . . memory, ⛁ . . . disks.

Parallel Database System Architectures

Shared disk DBMSs have many processors (with isolated memory) that share all disks (typically via a bus).

- \+ Scale to a larger number of processors.
- \- Communication between processors is slower (ms; bottleneck now at interconnection to disks).

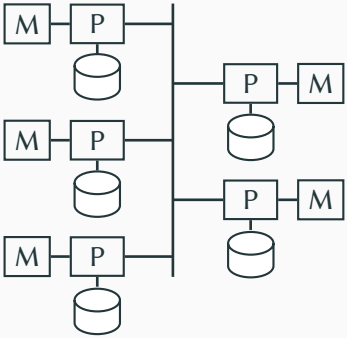


P . . . processor, M . . . memory, ⛁ . . . disks.

Parallel Database System Architectures

Shared nothing DBMSs have many processors with isolated memory and disk(s). The combination of a processor with isolated memory and disk(s) is also referred to as **node**.

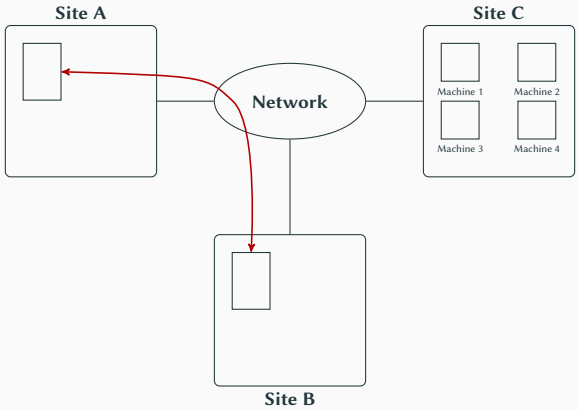
+ Scale to thousands of processors.
- Communication between processors is slow; access to non-local disk data is slow.



P … processor, M … memory, ⛁ … disks.

Distributed Database Systems

Distributed database management systems (DDBMSs) are DBMSs that operate on multiple machines that are located at geographically separated **sites**[14].



[14] A site can be imagined as a data center with multiple machines.

DDBMS vs. Shared-Nothing PDBMS

- Sites within a DDBMS are typically
  - **geograpically separated** (i.e., not a single data center)
    $\Rightarrow$ lower bandwidth (less throughput), higher latency (higher response time).
  - **separately administered** (i.e., retain some degree of autonomy).
- PDBMS can deal with node failures, whereas **DDBMS** can deal with **failures of entire sites** (e.g., due to natural disasters).
- DDBMS distinguish between **local** and **global transactions.**

Homogeneous vs. Heterogeneous DDBMS

A DDBMS is called **homogeneous** if the nodes share a common global database schema, perform the same tasks (e.g., run the same software), and actively cooperate in processing. Goal: View of a single database.

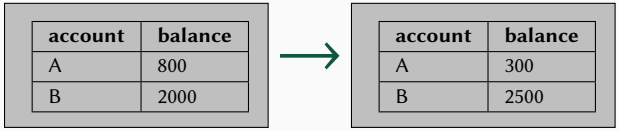
A DDBMS is called **heterogeneous** if the nodes have different schemata, perform different tasks (e.g., run different software), and may not be aware of other nodes. Goal: Integrate different databases.

Transactions

A **transaction** refers to a **sequence of operations** that accesses and (possibly) updates various data items. A transaction **transitions the database from one consistent state into another consistent state.**

Example: Transfer EUR 500 from bank account A to bank account B.

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```



Transactions

A DBMS must deal with **two major issues:**

- **System crash:** Software or hardware failures.
- **Concurrency:** Many different users may work at the same time (i.e., multiple transactions are executed).

A DBS implements particular consistency guarantees. Most relational DBMS manage transactions according to the so-called **ACID properties: A**tomicity, **C**onsistency, **I**solation, and **D**urability.

The ACID properties are considered **strong consistency guarantees.**

ACID Properties

Atomicity: Execute **all operations** of a transaction **or none** of them (*"all or nothing"*).

Example: Transfer EUR 500 from bank account A to bank account B.

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```

account	balance
A	800
B	2000

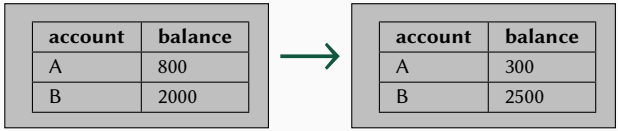
What happens if the system crashes after step 4?

ACID Properties

Consistency: After a transaction, all values in the database are correct (i.e., consistency is preserved).

Example: Transfer EUR 500 from bank account A to bank account B.

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```



What is a consistency constraint in the above example? A + B is the same before and after the transaction.

ACID Properties

Isolation: A transaction must be unaware of other simultaneously executing transactions (otherwise an inconsistent state may be encountered)[15].

Example: Transfer EUR 500 from bank account A to bank account B.

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```

What does `BEGIN; READ(A); READ(B); print(A + B); COMMIT` in between steps 4 and 5 print?

[15] For every pair of transactions T_i and T_j, it appears to T_i that either T_j finished execution before T_i started or T_j started execution before T_i finished.

ACID Properties

Durability: Successful transaction results persist in the database, even if the system crashes.

Example: Transfer EUR 500 from bank account A to bank account B.

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```

If the system crashes and the EUR 500 are lost, nobody is happy.

Transactions in PostgreSQL

3.4. Transactions

Transactions are a fundamental concept of all database systems. The essential point of a transaction is that it bundles multiple steps into a single, all-or-nothing operation. The intermediate states between the steps are not visible to other concurrent transactions, and if some failure occurs that prevents the transaction from completing, then none of the steps affect the database at all.

For example, consider a bank database that contains balances for various customer accounts, as well as total deposit balances for branches. Suppose that we want to record a payment of $100.00 from Alice's account to Bob's account. Simplifying outrageously, the SQL commands for this might look like:

```
UPDATE accounts SET balance = balance - 100.00
    WHERE name = 'Alice';
UPDATE branches SET balance = balance - 100.00
    WHERE name = (SELECT branch_name FROM accounts WHERE name = 'Alice');
UPDATE accounts SET balance = balance + 100.00
    WHERE name = 'Bob';
UPDATE branches SET balance = balance + 100.00
    WHERE name = (SELECT branch_name FROM accounts WHERE name = 'Bob');
```

The details of these commands are not important here; the important point is that there are several separate updates involved to accomplish this rather simple operation. Our bank's officers will want to be assured that either all these updates happen, or none of them happen. It would certainly not do for a system failure to result in Bob receiving $100.00 that was not debited from Alice. Nor would Alice long remain a happy customer if she was debited without Bob being credited. We need a guarantee that if something goes wrong partway through the operation, none of the steps executed so far will take effect. Grouping the updates into a *transaction* gives us this guarantee. A transaction is said to be *atomic*: from the point of view of other transactions, it either happens completely or not at all.

We also want a guarantee that once a transaction is completed and acknowledged by the database system, it has indeed been permanently recorded and won't be lost even if a crash ensues shortly thereafter. For example, if we are recording a cash withdrawal by Bob, we do not want any chance that the debit to his account will disappear in a crash just after he walks out the bank door. A transactional database guarantees that all the updates made by a transaction are logged in permanent storage (i.e., on disk) before the transaction is reported complete.

Another important property of transactional databases is closely related to the notion of atomic updates: when multiple transactions are running concurrently, each one should not be able to see the incomplete changes made by others. For example, if one transaction is busy totalling all the branch balances, it would not do for it to include the debit from Alice's branch but not the credit to Bob's branch, nor vice versa. So transactions must be all-or-nothing not only in terms of their permanent effect on the database, but also in terms of their visibility as they happen. The updates made so far by an open transaction are invisible to other transactions until the transaction completes, whereupon all the updates become visible simultaneously.

In PostgreSQL, a transaction is set up by surrounding the SQL commands of the transaction with `BEGIN` and `COMMIT` commands. So our banking transaction would actually look like:

```
BEGIN;
UPDATE accounts SET balance = balance - 100.00
    WHERE name = 'Alice';
-- etc etc
COMMIT;
```

Transaction Management

Programmers must ensure to properly define the transactions to preserve consistency.

A DBS typically includes a so-called **transaction manager**, which ensures that the transactions comply to the consistency guarantees (e.g., the ACID properties).

A transaction has **committed** if it completes successfully. Otherwise, the transaction is **aborted**. Undoing the changes of an aborted transaction is referred to as **rollback**.

Transaction Management – Atomicity

Before the DBS changes the database, it writes some information (transaction identifier, old/new values) about the changes into a so-called **log file.**

Example: Transfer EUR 500 from bank account A (EUR 800) to account B (EUR 2,000).

Transaction T_1:	Pseudo log file:	Database:
1. BEGIN		
2. READ(A)		
3. A = A - 500		
4. WRITE(A)	T1: OLD(A=800), NEW(A=300)	UPDATE(A=300)
5. READ(B)		
6. B = B + 500		
---[CRASH]---		ROLLBACK T1 on restart
7. WRITE(B)		
8. COMMIT		

Transaction Management – Isolation

Strict serial execution of concurrent transactions guarantees isolation, but severely limits the performance.

A **concurrency-control scheme** ensures that transactions can execute concurrently (i.e., their operations can be interleaved). Interleaving the operations of a transaction is called **schedule** and may result in a correct database state, or not!

A concurrent schedule is **serializable** if an equivalent serial schedule exists, i.e., the outcome of executing the transactions concurrently is the same as if they would have been executed serially.

Transaction Management – Isolation (Lock-Based)

Example: Transfer EUR 500 from bank account A (EUR 800) to account B (EUR 2,000).

Transaction T_1:

```
1. BEGIN
2. READ(A)
3. A = A - 500
4. WRITE(A)
5. READ(B)
6. B = B + 500
7. WRITE(B)
8. COMMIT
```

Transaction T_2:

```
1. BEGIN
2. READ(A)
3. A = A + 1,000
4. WRITE(A)
5. COMMIT
```

Database:

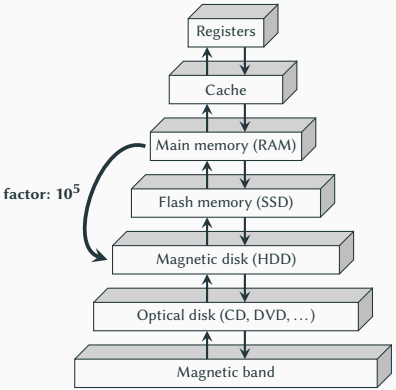
`LOCK(A, T1)`	OK
`UPDATE(A=300)`	
`LOCK(A, T2)`	**Conflict**
`LOCK(B, T1)`	OK
`UNLOCK(A, T1), UNLOCK(B, T1)`	OK

Transaction Management – Durability

Updating the persistent data may be postponed to improve performance, i.e., the data is provisionally updated in main memory (RAM). Data in main memory is volatile, i.e., it is lost on system restart.

Excursion: Nowadays, data can be considerd persistent if it is written to hard disk. DBMSs aim to be efficient/fast, thus they try to **avoid** or **postpone expensive/slow operations** like accesses to hard disk. Multiple data structures are maintained in main memory, which are commly referred to as **buffers.** The content of the buffers is **only written to disk if inevitable.**

Memory Hierarchy



< 1ns	Brain
> 1ns	Room
≈ 100ns	City
$\approx 100\mu s$	
≈ 10ms (10,000,000ns)	Pluto
> 1s	

Example: Transfer EUR 500 from bank account A (EUR 800) to account B (EUR 2,000).

Transaction T_1:	Pseudo log file:	Database:
1. BEGIN		
2. READ(A)		
3. A = A - 500		
4. WRITE(A)	T1: OLD(A=800), NEW(A=300)	postponed UPDATE(A=300)
5. READ(B)		
6. B = B + 500		
7. WRITE(B)	T1: OLD(B=2,000), NEW(B=2,500)	postponed UPDATE(B=2,500)
8. COMMIT		
		---[CRASH]---

Distributed Transaction Management

A DDBMS must consider additional aspects:

- **Distributed data storage** (replication and fragmentation).
- **Distributed transactions** (local and global).

Distributed Data Storage

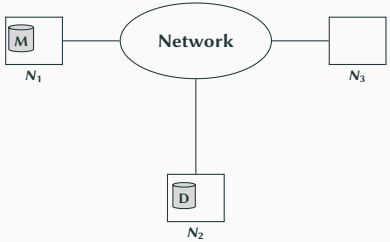
Assume the tables of our faculty database and the relational data model.

Members:

name	employment	department
Daniel Kocher	Postdoc	CS
Thomas Hütter	Postdoc	CS
…	…	…

Departments:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022
…	…	…

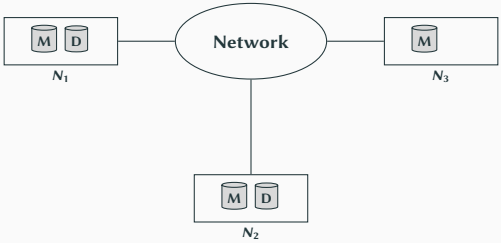


What if N_1 gets disconnected?

Distributed Data Storage – Replication

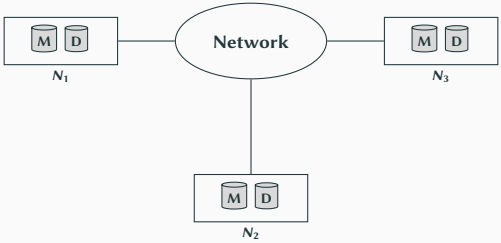
Replication: Data are **replicated** among multiple sites, i.e., a copy (replica) of the same data exists in different sites (intentional redundancy).

Example Replication:



Distributed Data Storage – Replication

Full replication: A copy of a relation is stored at **all sites**.

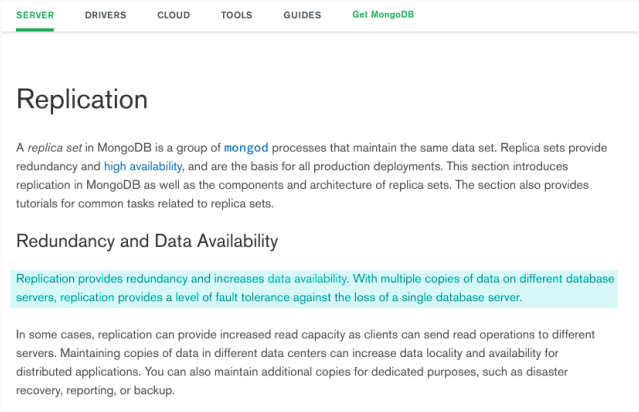


Fully replicated database: Every site contains a copy of the entire database.

Pros: Higher availability and performance, reduced data transfer.

Cons: Increased update costs and higher complexity of concurrency control.

Replication in MongoDB (Document-Based)



Distributed Data Storage – Fragmentation

Fragmentation: Data are **partitioned into fragements** stored at distinct sites, i.e., a specific part of the data is stored at a site.

Horizontal fragmentation: Relation is split row- or tuple-wise, and each row/tuple resides at a separate site. Allows **parallel processing** on **fragments** of a relation.

Vertical fragmentation: Relation is split into smaller subschemata (based on the columns/attributes), and each subschema resides at a separate site. Allows **parallel processing** on a **relation**.

Example Horizontal Fragmentation

Members M1:

name	employment	department
Daniel Kocher	Postdoc	CS
Thomas Hütter	Postdoc	CS

Members M2:

name	employment	department
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS

Members M3:

name	employment	department
Simon Kirchgasser	PhD Student	AIHI
Roland Kwitt	Full Prof.	AIHI

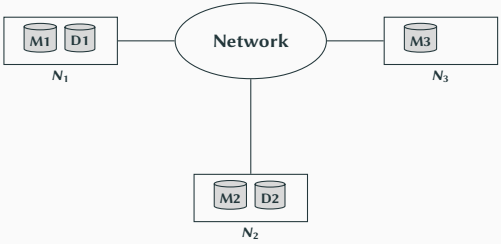
Departments D1:

name	location	year
CS	Science City Salzburg	2022
AIHI	Science City Salzburg	2022

Departments D2:

name	location	year
GI	Science City Salzburg	2010
Math.	NAWI	1967

Example Horizontal Fragmentation



Members M1:

name	employment	department
Daniel Kocher	Postdoc	CS
Thomas Hütter	Postdoc	CS

Members M2:

name	employment	department
Tijn De Vos	PhD Student	CS
Christoph Kirsch	Full Prof.	CS

Members M3:

name	employment	department
Simon Kirchg.	PhD Student	AIHI
Roland Kwitt	Full Prof	AIHI

Distributed Data Storage – Fragmentation

Horizontal and vertical fragmentation can be **mixed.** In any case, the fragmented data must be **reconstructable.**

Pros: Higher performance (parallel processing), better locality (reduced data transfer).
Cons: Increased costs on site failure and if data is retrieved from different sites.

Distributed Data Storage – Replication, Fragmentation, and Transparency

Fragmentation and **Replication** can be **combined:**

- Relation is partitioned into several fragments.
- System maintains several identical replicas of each such fragment.

Data Transparency: User may be unaware of how and where data items are stored.

- Fragmentation transparency
- Replication transparency
- Location transparency

Distributed Transactions

Local transactions access/update data at only one (local) site. A local transaction manager enforces the ACID properties.

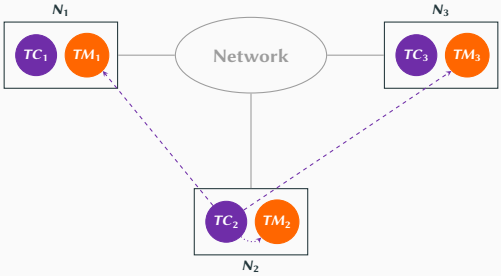
Global transactions access/update data at multiple (local) sites. Local subtransaction are executed at each site. Enforcing the ACID properties is much more complex.

Each site has a **local transaction manager** and a **transaction coordinator.**

Distributed Transactions

The **local transaction manager** ensures that the ACID properties hold for local transactions and maintains the local log files.

The **transaction coordinator** starts transactions that are initiated at one site, distributes the subtransactions to other sites, and ensures that a transaction either executes **at all sites or at none.**



Distributed Transactions – Commit Protocols

Required because we must ensure **atomicity across all sites**, e.g., we are not allowed to commit a transaction at node N_1 but abort the same transaction at node N_2.

List of Protocols:

- Two-Phase Commit (2PC; used in practice).
- Three-Phase Commit (3PC; solves issues of 2PC but impracticable).
- Persistent Messaging (PM).

Distributed Transactions – 2PC in a Nutshell

Transaction T is initiated at node N_i with transaction coordinator TC_i.

Phase 1: TC_i "asks" other participants to **prepare to commit** (and logs it beforehand). Each **transaction manager** determines if **it can commit**, logs it, and "reports" it to TC_i.

Phase 2: If TC_i receives a **single abort** message, then all participants are **informed to abort *T***. Otherwise, all participants are **notified to commit** T. Prior to that, TC_i logs the decision locally. The involved transaction managers comply to the decision.

Consistency

Different notions of consistency to specify desired properties in a DDBMS. Ideally, all updates appear immediately **at all sites** in the same order (illusion of a single data copy).

Strong consistency refers to this ideal scenario, but this is often expensive (or even impracticable). **Weak consistency** relaxes the consistency constraints to improve the performance or the availability of a DDBMS.

Availability

High Availability: A DDBMS with extremely low downtime (about 99.99% available).

In large systems, a failure happens frequently (nodes may be down or the network may partition).

Trade (or sacrifice) consistency in order to achieve **high availability.**

Brewer's CAP Theorem

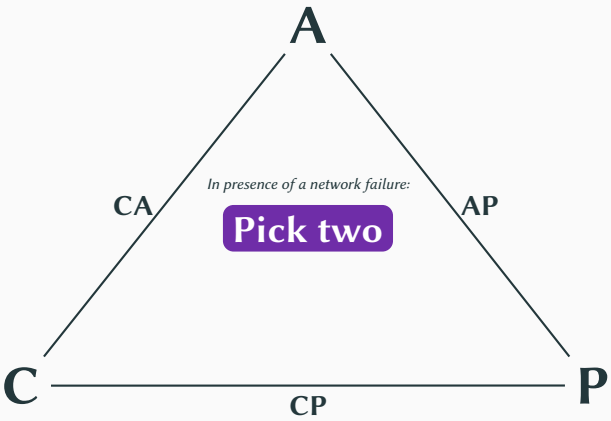
A distributed database system has three properties:

- **C**onsistency: All replicated copies are in the same state.
- **A**vailability: System runs even in case of failures due to replication.
- **P**artition-tolerance: System runs even if the network is partitioned.

Network partition: Network decomposes into multiple parts/subsystems that cannot reach one another.

CAP Theorem: You can have **at most two** of the three **properties.** Precisely, in **case of an error**, one of the 3 properties **C**onsistency, **A**vailability, or **P**artition-tolerance is lost.

Brewer's CAP Theorem



Brewer's CAP Theorem

AP Systems: Sacrifice consistency in case of a network **P**artition, but stay **A**vailable. Inconsistencies must be resolved once the network partition is resolved.

CP Systems: Sacrifice availability in case of a network **P**artition, but maintain **C**onsistency.

CA Systems: "Ideal" **C**onsistency and **A**vailability. No availability and consistency guarantees in case of a network partition.

Reality: AP or **CP**

- CP and CA systems are similar since CA systems are unavailable if the network partitions.
- Network partitions are rare but unpredictable.
- **Question:** How does the DDBMS trade **C**onsistency and **A**vailability if network partitions?

Abadi's PACELC Theorem

PAC stands for CAP (rewritten) and covers the DDBMS properties in case of an error. **ELC** stands for **E**lse (DDBMS is running without error): How does the DDBMS trade **L**atency and **C**onsistency?

PACELC [16][17][18] **extends** CAP and considers the tradeoff between **L**atency and **C**onsistency that a DDBMS has to make when it **operates regularly.**

Even if a DDBMS operates without failure, we have a **tradeoff** between **L**atency and **C**onsistency. This is **due to data replication** that is a prerequisite for high availability.

[16] https://en.wikipedia.org/wiki/PACELC_theorem
[17] http://dbmsmusings.blogspot.com/2010/04/problems-with-cap-and-yahoos-little.html
[18] http://www.cs.umd.edu/~abadi/papers/abadi-pacelc.pdf

The BASE Properties

BASE is an **alternative consistency model** that is **not as strict** as the ACID properties and favors **availability over consistency.**

Basically Available: The system appears to **work most of the time**, i.e., reads/writes should be allowed even if the network partitions, but without consistency guarantee.

Soft State: The **state** of the database **may not be precisely defined** all the time, i.e., replicas do not have to be mutually consistent (e.g., in case of writes).

Eventually Consistent: Once the network partitioning is resolved, the states of all replicas converge, i.e., all **replicas become consistent eventually** (i.e., over time).

Eventual Consistency

No new updates $\Rightarrow$ Writes are propagated to all replicas and all replicas converge towards a common state.

Inconsistent replicas must be identified because two replicas may be updated independently (e.g., version-vector scheme).

Inconsistent updates may need to be **merged** (e.g., in the worst case, human interaction is required – comparable to a merge conflict in `git`).

Workloads

With regard to database systems, a **workload** is a set of queries/updates that reflects a **typical usage pattern (load).**

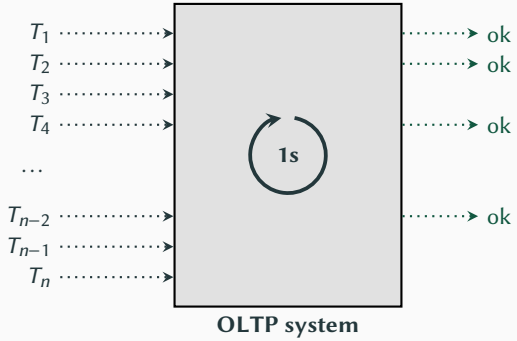
Different database systems perform better/worse on particular workloads.

Transaction Processing Performance Council (TPC): An independent consortium that releases standardized benchmarks for various workloads, the TPC benchmarks [19].

[19] `http://www.tpc.org/`

OLTP Workloads

Online Transaction Processing (OLTP): Short-lived read/write transactions with a small footprint (i.e., only a small portion of the data is touched). **Many transactions** must be processed **as fast as possible** (high throughput, low response time). The TPC-C benchmark provides typical OLTP workloads.

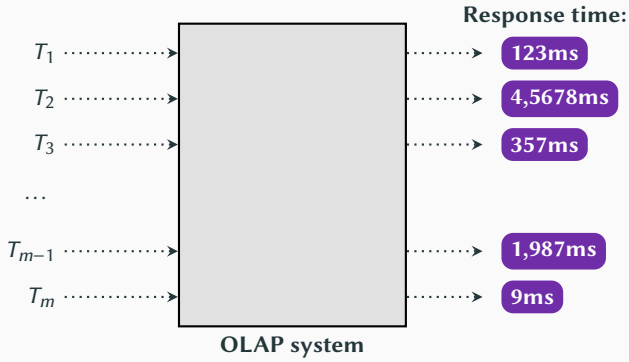


Throughput:

123,456 trans./sec.

OLAP Workloads

Online Analytical Processing (OLAP): Long-running read-only queries that exploratory analyze a large portion of the overall data (to support decisions). This often involves complex join operations and the main focus is **low response time.** The TPC-DS benchmark provides typical OLAP workloads; "Data Warehouse".



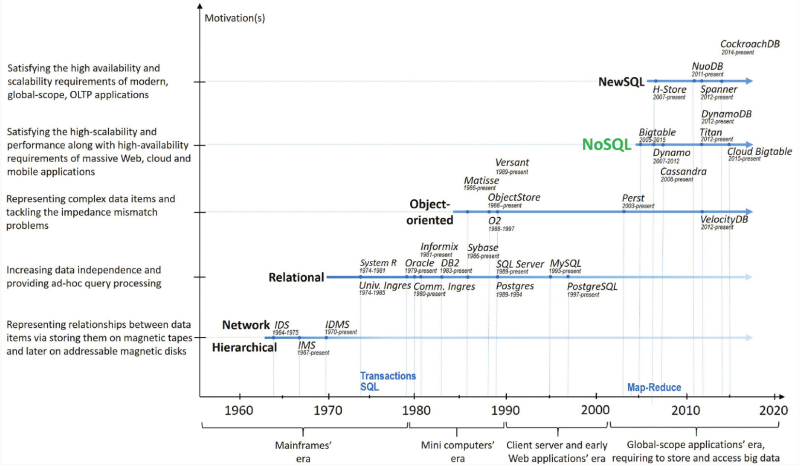
Workloads – Batches vs. Streams

Batch Workloads: A **batch** is a large but **bounded static dataset.** Before data can be processed, all data must be completely available (e.g., on hard disk).

Stream Workloads: A **stream** is an **unbounded evolving dataset.** Data items are processed as they stream into the system one after another, i.e., the data does not have to be completely available.

Systems Potpourri

Continuous Development



Picture taken from Davoudian et al. *A Survey on NoSQL Stores.* ACM Computing Surveys, 2018.

In-Memory Database Systems: Relies on **main memory (RAM) for storing the data** rather than hard disks (HDDs) or SSDs. Very **low response times (microseconds)** but must deal with durability (logs).

Database as a Service (DBaaS): A cloud-based platform (service) that provides computing infrastructure, data storage ,and **database functionality in the cloud.** The clients (you) do not have to set up their own database system on their own hardware, but just **access and use a database that runs in the cloud.**

Key-Value Stores – Redis

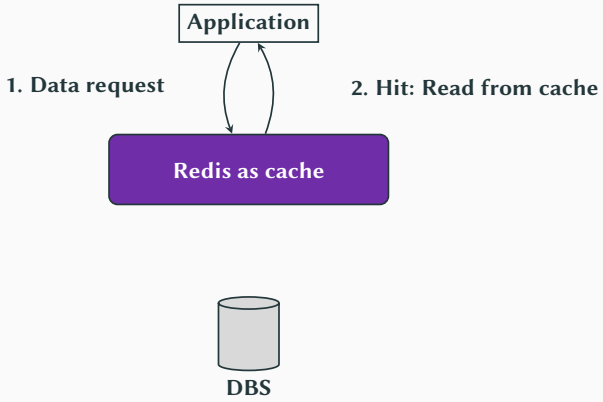
The **RE**mote **DI**ctionary **S**erver [20] is an **in-memory** NoSQL database system based on the **key-value data model** that **supports durability** (i.e., data can be made persistent).

- Redis is a CP system.
- In-memory, i.e., very fast (avg. read/write performance: < 1ms).
- Collection of useful, high-performance data structures (lists, sets, bitmaps, …).
- Replication and persistence support.
- Supports many programming languages incl. Java, Python, C/C++, and JavaScript.

[20] `https://redis.io`

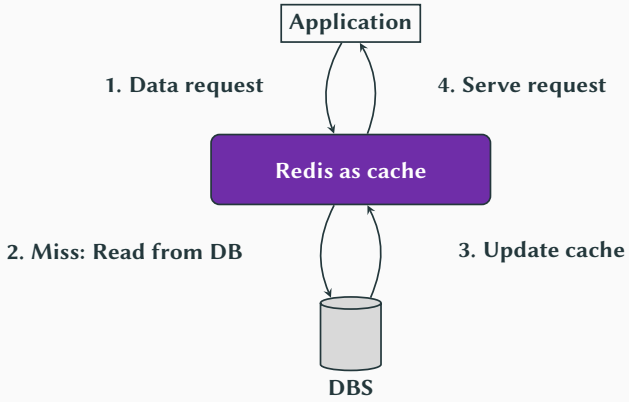
Key-Value Stores – Redis

Use Case: **Cache** between application and database system – **Cache Hit**.



Key-Value Stores – Redis

Use Case: **Cache** between application and database system – **Cache Miss**.



Key-Value Stores – Other Systems

Riak KV [21] is a distributed **persistent** key-value store with support for **advanced data types** (e.g., JSON). It is inspired by Amazon's DynamoDB [22] and provides **high availability** (i.e., is an AP system).

Memcached [23] ("Mem-Cash-Dee") is a distributed **in-memory** key-value store with a performance similar to Redis. However, Memcached supports only the **simple key-value data model** and has **no support for durability.** Not a database system!

[21] https://riak.com/products/riak-kv/
[22] https://aws.amazon.com/dynamodb/
[23] https://memcached.org/

Document Stores – MongoDB

MongoDB [24] is a distributed NoSQL database system based on the document-oriented data model with a focus on consistency, high read availability, and horizontal scalability.

- MongoDB is a CP system (single leader based system).
- Uses JSON as document format (specifically, a binary JSON format called BSON).
- Shared-nothing system architecture.
- JSON-based query language (limited support for joins as we know it).
- Replication and sharding (aka fragmentation) support through replica sets.

[24] https://www.mongodb.com/

Document Stores – Other Systems

Apache CouchDB [25] is a distributed document store with support for **master-master replication** [26] and a conflict resolution protocol. It is an AP system that uses the plain JSON format.

Couchbase [27] is a distributed document store with a built-in in-memory cache (memcached) and an SQL-like query language (N1QL). It uses CouchDB as back end.

[25] https://couchdb.apache.org/
[26] https://en.wikipedia.org/wiki/Multi-master_replication
[27] https://www.couchbase.com/

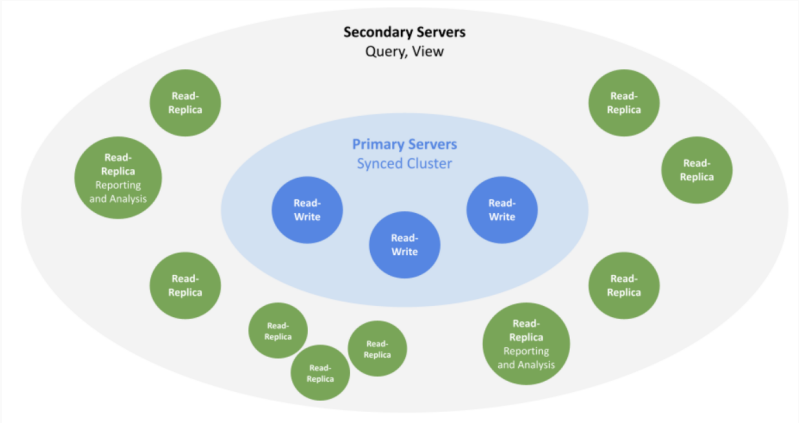
Graph Stores – Neo4J

Neo4j [29] is a NoSQL database system based on the graph data model with ACID guarantees. Neo4j is a **native** graph store.

- Neo4j is a CP system (as of version 3.5).
- Shared-nothing system architecture.
- Set of core servers (serve write+read) and many read replicas.
- Emphasis on read availability (full replication).
- SQL-inspired query language (Cypher) to describe graph patterns (ASCII art).

[29] https://neo4j.com/

Graph Stores – Neo4j



https://neo4j.com/docs/operations-manual/current/clustering/introduction/.

Graph Stores – Other Systems

Tigergraph [30] is a distributed native graph store that supports parallel computation and advanced analytics. It has its own query language GSQL.

ArangoDB [31] is a multi-model database system that supports the graph-based model in JSON format.

OrientDB [32] is another multi-model database system that supports the graph-based model. It uses an SQL-like syntax that is extended for graphs.

[30] https://www.tigergraph.com/
[31] https://www.arangodb.com/
[32] https://orientdb.org/

Extensible Record Store – Apache Cassandra

Apache Cassandra [33] is a distributed NoSQL database system based on the extensible record (or wide column) data model. It is a decentralized and "master-less" DDBMS that supports eventual consistency.

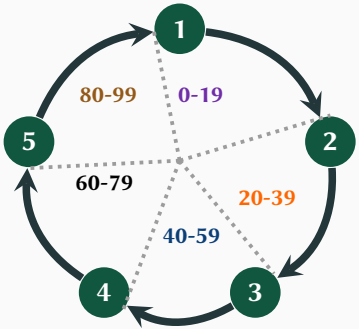
- Apache Cassandra is an AP system (but can be configured as CP system).
- Shared-nothing system architecture.
- Support for nested column families (so-called super column families).
- The Cassandra query language (CQL) resembles SQL.

[33] https://cassandra.apache.org/

Extensible Record Store – Apache Cassandra

Master-less architecture $\Rightarrow$ **No single point of failure.**

Consistent Hashing (Token Ring)



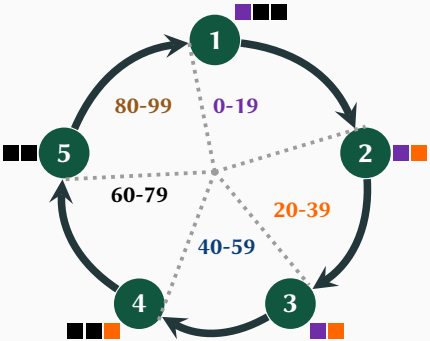
Hash function $h(.)$ determines node.

Data			$h(.)$	Node
Daniel	Kocher	Postdoc	18	**1**
Thomas	Hütter	Postdoc	21	**2**
Tijn	De Vos	PhD Student	67	**4**
Christoph	Kirsch	Full Prof.	70	**4**

Extensible Record Store – Apache Cassandra

Master-less architecture ⇒ **No single point of failure.**

Replication Factor (for example, 3)



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Christoph	Kirsch	Full Prof.	70	4

Other Systems

- **RDBMS:** PostgreSQL [34], SQLite [35], Oracle [36], Microsoft SQL Server [37], …
- **NewSQL Systems:** CockroachDB [38], VoltDB [39], …
- **In-Memory OTLP & OLAP Systems:** HyPer [40], SAP Hana [41], …
- **Cloud Services:** Amazon DynamoDB [42], Snowflake Cloud Data Warehouse [43], …

[34] https://www.postgresql.org/
[35] https://www.sqlite.org/
[36] https://www.oracle.com/database/
[37] https://www.microsoft.com/en-us/sql-server/sql-server-2019
[38] https://www.cockroachlabs.com/
[39] https://www.voltdb.com/
[40] https://hyper-db.de/
[41] https://www.sap.com/products/hana.html
[42] https://aws.amazon.com/dynamodb/
[43] https://www.snowflake.com/

Additional Material

Use the **database of databases** [44] for a first impression and cross references.

A 37-page **survey on NoSQL database systems** [45].

Books on NoSQL database systems [46] [47].

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[44] `https://dbdb.io/`

[45] Davoudian et al. *A Survey on NoSQL Stores.* ACM Computing Surveys, 2018.

[46] Sadalage and Fowler. *NoSQL Distilled – A Brief Guide to the Emerging World of Polyglot Persistence.* Addison-Wesley, 2013.

[47] Redmond and Wilson. *7 Databases in 7 Weeks - A Guide to Modern Databases and the NoSQL Movement.* Pragmatic Bookshelf, 2012.